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Self-Swarming for Multi-Robot Systems Deployed for Situational Awareness

Fabrice Saffre and Hanno Hildmann and Hannu Karvonen and Timo Lind

Abstract Machine-based situational awareness is a key element to conscious and intelligent interaction with the complex world we live in, be it for the individual unit, a complex dynamical system, or even complex systems of systems. To create this awareness, the frequent gathering of accurate and real-time intelligence data is required to ensure timely, accurate, and actionable information. Unmanned aerial vehicles (UAVs) and other semi-autonomous cyber-physical systems are increasingly among the mechanisms and systems employed to assess the state of the world around us and collect intelligence through surveillance and reconnaissance missions. The current state of the art for humanitarian and military operations is still relying on human-controlled flight/asset operations, but with increasing autonomous systems comes an opportunity to offload this to the devices themselves. In this paper, we present a principled and expandable methodology for evaluating the relative performance of a collective of autonomous devices in various scenarios. The proposed approach, which is illustrated with drone swarms as an example use case, is expected to develop into a generic tool to inform the deployment of such collectives, providing the means to infer key parameter values from problem specifications, known constraints, and objective functions.

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1 Introduction

Much has been written about the importance of accurate information, considered by some to be *"power and currency of the virtual world we inhabit"* [11]. There are classes of applications where the availability of timely, accurate, and actionable information is a key pre-requisite to a successful handling of the situation. In the (civilian) context of civil security and public defence this is the case, for example, for large events or events where complex interactions between participants can lead to problematic behaviours (crowd control [48], evacuation management [32]) or in the aftermath of a natural disaster (earthquake, flooding, large forest fires, etc. [1]).

In the military domain, the need for high-quality information sources is found in virtually all aspects of operations. *Drones*, or Unmanned Aerial Vehicles (UAVs), have been used as civilian or military surveillance tools, to patrol borders for trespassers and smugglers or to watch for enemy infiltrations [31].

Fig. 1 A TNO reconnaissance drone departing for automatic threat evaluation for border security and surveillance as part of the (now concluded) EU funded ALFA (Advanced Low Flying Aircrafts Detection and Tracking) project [46].

1.1 Civilian and military use of UAVs for information gathering

The umbrella term applied to all intelligence functions for military operations is *Intelligence, Surveillance, and Reconnaissance (ISR)*, which originally was performed by humans, but for a number of reasons (reliability, timeliness, consistency, etc) this is sub-optimal. The observation of an expansive geographical area over an extended period of time [36] is almost certainly going to be problematic [43]. This could be because it is uneconomical to station a dedicated human force and keep it supplied in a remote, hard-to-reach place, or because environmental conditions are harsh or hazardous, making it a difficult assignment.

Polar [9] or tropical environments, e.g., are notoriously hard to navigate for humans and UAVs have been used for data collection in such environments with outstanding results [23]. In addition, there are dedicated wildlife areas [33] where, in addition to the difficult accessibility of the terrain, restrictions apply to the presence of humans. Yet precisely because they are remote, many of these regions are crossed by international borders or are home to vulnerable ecosystems, both of which make constant and diligent monitoring an obvious requirement. This creates the almost perfect use-case for autonomous drone-based surveillance [31].

1.2 Using autonomous UAVs as well as swarms thereof

For ISR and, in general, for decision support, information is commonly aggregated from many different sources [47], and UAVs are ideally suited for this task. With increasing levels of autonomy becoming achievable thanks to progress in Artificial Intelligence (AI) and related fields, missions that could conceivably be carried out by UAVs without any human intervention are rapidly growing in number. Of particular interest are self-organizing [10] groups of autonomous UAVs (drone *swarms*) that could be deployed concurrently and act as a team in the pursuit of complex, abstractly defined objectives [3]. One promising field of application for this fast-maturing technology is ISR, or *surveillance* in the civilian domain [21]. There, the use of collectives of cyber-physical systems (e.g., UAVs) operating as a single unit is increasingly considered [22]. Within ISR there is a strong focus on mission planning and scheduling for various types of assets, such as e.g., ground based units, UAVs or satellites [14]. The literature on collaborative multi-robot systems [12, 24, 7, 25] used as Mobile Sensing Platforms (MSPs) is growing fast [15, 17, 21, 22], with sub-areas developing for complex problems such as task allocation [28], multi-robot task allocation [7], group formation [42] and, more generally, self-organization [24].

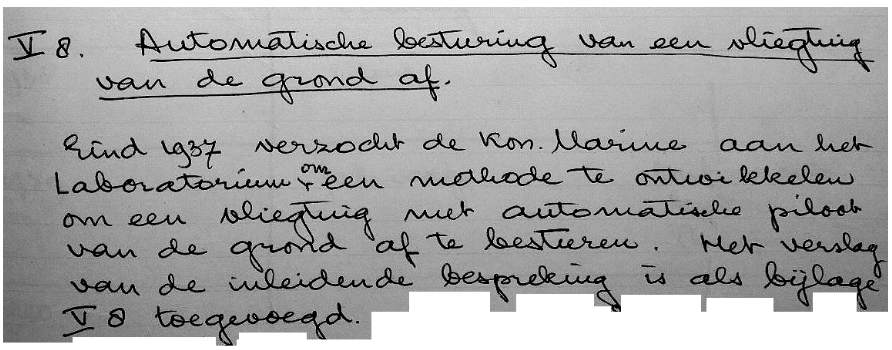
Overview

Section 2 briefly discusses our stance on the use of UAVs as MSPs and provides some examples for the uses of drones at the Technical Research Centre of Finland (VTT) and the Netherlands Organisation for Applied Scientific Research (TNO). We argue for taking a biologist's view on UAV swarms (including a warning) and then elaborate on a number of aspects and challenges inherent to Multi-Robot Systems (MRSs) / Multi-Agent Systems (MASs). In Section 3 we define a variation of the self-swarming for Situational Awareness (SA) application (the problem) as well as propose a solution for it. Before evaluating our approach, Section 4 details the models used, the performance measures, and the implementation / methodology used to generate the results. With this in place, Section 5 provides comparative results as well as a discussion thereof.

The interested non-technical reader may immediately want to skip ahead to the conclusion (Section 6) where we hope to provide a concise summary of our work, situate it inside the application landscape and, building on this, provide an outlook over how this (theoretical result) will be used in future projects.

2 Background

VTT provides a wide set of services [30, 44] and solutions [27] to UAV systems and has deep knowledge of modern UAV components, such as batteries, materials and sensors. Several next generation new autonomous drone use-cases are hosted by VTT, including projects in the areas of 5G and cyber security. At TNO, research in drone technology started as early as 1937 (see Figure 2, courtesy of TNO Museum Waalsdorp[1]) and today, dozens of research groups across all units use drones.



V 8. Automatische besturing van een vliegtuig van de grond af.

Eind 1937 verzocht de Kon. Marine aan het Laboratorium om een methode te ontwikkelen om een vliegtuig met automatische piloot van de grond af te besturen. Het verslag van de inleidende bespreking is als bijlage V 8 toegevoegd.

Fig. 2 TNO has been active in drone research for more than 80 years. Shown: entry (in Dutch) in the reconstructed lab records by Van Soest in 1947 and archived at TNO Museum Waalsdorp. Translation (by Eric Luiijf, TNO): *"At the end of 1937, the Royal Dutch Navy requested the lab* [TNO] *to develop a method to control a sea plane* [...] *from the ground"*.

2.1 UAVs as Mobile Sensing Platforms

The usage of UAVs as MSPs [5, 15, 16, 20, 21, 26, 33] or as Wireless Senor Network (WSN)-nodes [17, 41] is growing in popularity in the literature. With regard to single UAV usage, in Figure 1 a drone is departing for a Beyond Line of Sight (BLOS) flight [46], Figure 3 shows a drone performing a geological survey [40].

[1] https://www.museumwaalsdorp.nl/en/radiocommen/telecommunication-remote-control-of-a-plane-1938-1940/

Fig. 3 UAV-use for geology [40]. The corresponding report can be found in [29]

Due to the recent advances in the corresponding technologies [41], decreasing unit-cost is making the operation of collectives of UAVs increasingly feasible [7], with Search and Rescue (SAR) operations being one of the dominant application domains for UAV swarms [24, 37, 45]. Legal restrictions [26], still make the practicality of operation a drone swarm in civilian airspace very difficult, but for projects such as SWACOM[2] we have access to non-civilian airspace (see Figure 4).

Fig. 4 A field-demonstration (conducted outside civilian airspace) for the SWACOM (Swarming and Combat Management, a project by Thales Nederland B.V., TNO-DSS and branches of the Dutch Military) project, where multiple heterogeneous devices collectively find, and identify, objects that can pose a threat to either units in the field or to civilians.

2.2 The swarm is more than the sum of its drones

The argument for the use of UAVs no longer needs to be made, the literature speaks for itself, e.g, [4, 32]. With advances in the related technologies, the use of multiple UAVs as a single, physically disjunct, unit is increasingly considered in the literature, e.g., [2, 19, 20, 21, 22, 38]. Using a term borrowed from biology, such collectives are commonly referred to as a *swarm* [20].

[2] https://www.youtube.com/watch?v=epCXIYpMSFw&t=13s

UAV swarms offer a number of advantages over the use of a single, larger, more costly, UAV [19] which range e.g., from overcoming physical challenges (the curvature of the earth restricts the communication between a ground station and an aerial unit, this is less the case between two aerial units), operational bounds (multiple drones can replace their peers when these need to land for charging) over practical considerations (such that smaller units are harder to spot for the enemy) to financial constraints (smaller drones cost significantly less, both in Capital Expenditure (CAPEX) as well as in Operational Expenditure (OPEX)).

It should be noted that (as always) there is no proverbial *silver bullet*. UAV swarms, while offering many advantages, also have the potential for poorer results [25], if their design is not done well. Therefore, the authors would like to offer words of caution in regard to the use of swarming and other phenomena observed in biology: whenever considering such concepts from the field of biology, the practitioner should bear in mind that any such phenomena exists for a purpose (having evolved through selective processes to come into existence in the first place). Unless we (a) understand this *raison d'être*, and do so (b) within the appropriate context and environment, designing concepts from biology into cyber-physical systems is merely an act of doing things for the sake of doing them. Particularly with regard to swarming, the ability for group of devices to exhibit coordinated movement through collective decision [13] has occasionally been regarded as its own reward [6], notwithstanding its usefulness in a practical application scenario.

2.3 Digital Twins

The approach used in this paper is inspired by the way in which social insects use their environment as a shared memory. Since our locations do not actually emit pheromones, we keep track of this in a digital representation of the environment. We use a centralized memory (in the control centre) to mirror the corresponding effect a drone's path would have on the environment. In other words, we maintain a computer based model of the real world, a so-called Digital Twin (DT).

DTs [34] are essentially virtual (thus, digital) replicas of physical systems or environments [8], with maybe the most famous example being NASA's replication of the Apollo 13 capsule on earth to assist the astronauts in space looking for a solution, given their specific circumstances and available resources. The use of DTs has become widely popular in the industry in recent years [18], especially in the context of real-time prediction, optimization, monitoring, controlling, and enhanced decision making capabilities [39]. They are considered a technology trend and a disruptive engineering approach [34], not the least due to their potential to effortlessly integrate data (bi-directionally) between the real (physical) and the digital (virtual) version or model of a machine [18].

3 Describing the Problem and the Solution

As discussed, real-time data collection capability can be a critical factor for many applications [33], be it in the civilian [12] or in the military domain [35]. In this paper, we propose a generic and theoretical solution to an abstract problem. As such, the presented approach constitutes the first step towards a more domain, and application, -tailored solution (see Section 6 for future work).

3.1 Problem definition and specification

The problem falls into the category of MRS task allocation [7, 12, 24, 25], specifically the continuous assignment of sets (sequences) of tasks (locations) to members of a swarm, over time. A collective of cyber-physical systems (a UAV swarm) is tasked with providing information about a large area; their performance is assessed through a *freshness*, summed up for all locations under surveillance.

The problem is kept generic, we distinguish the following problem-defining characteristics, expressed formally through a number of tunable parameters:

- **The environment** is reduced to three parameters or functions, namely the number of unique locations in the environment, how these locations are connected to one another and the physical distance between the locations.
- **The bases** where the agents (UAVs) can recharge their batteries. For those, both their number as well as location is relevant.
- **The drones** are defined by their number, a function assigning them to starting bases and their maximum range (referred to as the *autonomy*-value).
- **Permissible actions**, which in our case are simply *being present* at a location, which has the effect of resetting the signal intensity there to zero.

3.2 The Objective

The objective is to identify and fine-tune a local (per drone) decision-making algorithm so that the resulting collective swarm of drones exhibits collective artificial intelligence as a self-organising swarm. The main difference with related work on this topic is the scale of the desired response, both in time and in space.

The goal is not to elicit a collective motion pattern such as flocking or schooling in a small environment (where the agents or particles operate in close proximity and directly interact with each other through, e.g., collision avoidance and/or trajectory alignment mechanisms) and over a short characteristic time scale (seconds or minutes). Instead, our objective is to develop a method that allows a swarm of drones to perform a (set of) task(s) collectively and autonomously in a very large space (square kilometres) and for an unlimited duration (weeks, months or years).

While we use the distance measure of kilometres, the dimensions of the environment scale (up or down) with the performance of the devices as well as the size of the swarm. While the use case discussed is the surveillance of a national park using large drones, this could equally be applied to e.g., the management of a commercial port (Rotterdam, Hamburg, etc) using smaller drones (or autonomous surface vessels).

Within that, the performance of the swarm has to be maximised collectively, through implicit coordination between individual units. For example, two drones patrolling the same area at the same time is suboptimal and we want to reduce this using as little inter-drone communication as possible. In addition, the work is intentionally kept generic, but this gives rise into a number of sub-problems: navigation in an arbitrary topology, information exchange between drones, response to faults and other unexpected events etc.

3.3 The approach

The core concept is that devices plan their paths individually, and based on their own perception of the environment only. Taking inspiration from biology, the underlying view taken is that each location emits a signal which, as it accumulates, can diffuse into neighbouring locations. The signal intensity represents the age of the information about the corresponding location and is reset to zero when a drone visits. However, since this signal has no physical existence in the real world, the system (the set of all bases) collectively maintains a shared memory (of signal levels), to which any drone can write / from which it can read, *while at a base*. Therefore the drones operate in a way that somewhat resembles the behaviour of certain social organisms such as honeybees who share information about their environment with their peers when gathering inside the hive.

Coordination between drones is achieved indirectly, through what amounts to a DT: a real-time simulation of the monitored area in which the production and diffusion of a virtual signal can be used to influence the collective response of the swarm. The underlying assumptions are that (1) this simulation is running continuously and (2) the current state of the world's DT is accessible by drones at every base (so it can be used for path planning). This is not particularly difficult to achieve, but it requires two-way communication between the bases, so that the overall picture (local intensity of the signal at all locations) remains up-to-date throughout the system. The signal differs from what is usually called a *pheromone* in that it is not generated by the agents themselves but on the contrary, is produced at a fixed rate at every location in which none is present.

3.4 The solution

We propose a solution in which each drone determines for itself where to go, and when. It does so, based on model maintained by the DT and while landed at a base.

This means that (a) drones determine their next path (a) in advance (always while landed and before they take off again) and that (b) this path is constructed based entirely on the information about the world, as maintained by the DT. Before taking off, the UAV flies its intended path with the DT which updates its model *as if the drone had already completed its journey*.

The main advantage of this approach is that it does not require any communication between units - or between units and bases - during the flight. The main drawback is that, once a route has been selected and the drone has departed, it can no longer be modified through exogenous means. The control loop - executed by each drone - distinguishes a number of stages:

1. **At base & charging:** drones will charge until their battery is full.
2. **Charged & ready:** after reaching full charge, a drone enters a *resting* state out of which it will come with a fixed probability per predefined time period.
3. **Planning a route:** a UAV has a maximum range (the number of transitions from one location to another in a discretised world map a drone can make with a single battery charge). Planning happens in two stages:

    a. *outbound:* while the last location in the currently planned route is fewer hops from the nearest base than the remaining autonomy, consider all neighbours of the last location in the route and use a function to pick the next location to visit. This decision is using the signal levels of the neighbouring locations, either deterministically (picking always the one with the highest intensity) or stochastically with a variable non-linear component (the stronger the signal from a location, the higher the chance of it being chosen as next hop). The current implementation uses the deterministic variant, with investigations into the performance of a stochastic choice left for future work (see Section 6).
    b. *inbound:* once the distance to the nearest base reaches the same value as the remaining autonomy, the UAV becomes restricted in the choice of its next destination. In short: it uses the same method to determine the next hop as before, but this time only those locations that reduce the number of hops to a base are considered. NB: this means that a drone can return to the base from which it started or head for a different one.

4. **Departure:** before the UAV departs, it updates the DT which treats the plan as *fait accompli* and resets the signal intensity for all locations in the flight path to zero. The drone then performs its flight autonomously and only reconnects to the system after it has landed at the next base.

Resetting he intensity of the signal in the DT immediately along the entire route prior to the drone's physical departure has two advantages: (1) it makes it easier to implement, since all updates are made in one go and without the need for any interaction with airborne units, and (2) it means that distant waypoints along the route become less attractive to other drones planning their own patrol immediately (i.e. before they are even reached by the departing unit). Point (2) tends to limit duplication of effort by reducing overlap between waypoint sequences. The idea behind the approach is briefly illustrated in Figure 5 on the next page.

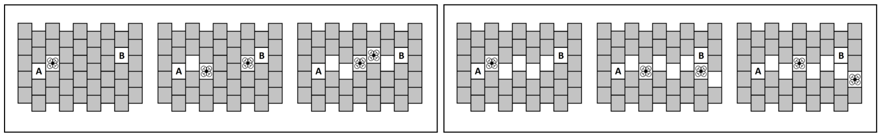


Fig. 5 Illustrating the benefit of *immediately* resetting the signals along the entire path (right image), as opposed to doing so per location, when visiting that location (left image). The first drone starts in base A, and is planning to move to base B. In the left sequence, signals are only removed from a location when the drone moves there. In this situation, a second drone (in base B) may plan the exact same route - only in reverse (from base B to base A) which is effectively redundant.

4 Materials and Methods

4.1 The world

The map is discretised using a hexagonal mesh. This choice ensures that the distance between any two neighbours (candidate way points) has the same value for all connections (in our simulations this value is set to 1). A distance of 1 can be understood as 100 *meters* to allow some comparison to the real world.

Maps are generated by creating the hexagonal mesh equivalent of a 5 *km* square ($25km^2$), fully connected, and then iteratively removing nodes randomly, starting from the outer edge (i.e., only nodes with less than 6 neighbours can be removed) to generate a realistically complex geographical area to *patrol*. A sample of 1000 such regions was created and used consistently throughout all simulations. The final sample was comprised of 995 regions (5 had to be discarded due to their being disconnected) varying in size from just above 2 to just under $21km^2$.

Figure 6 shows two representative examples of a typical layout.

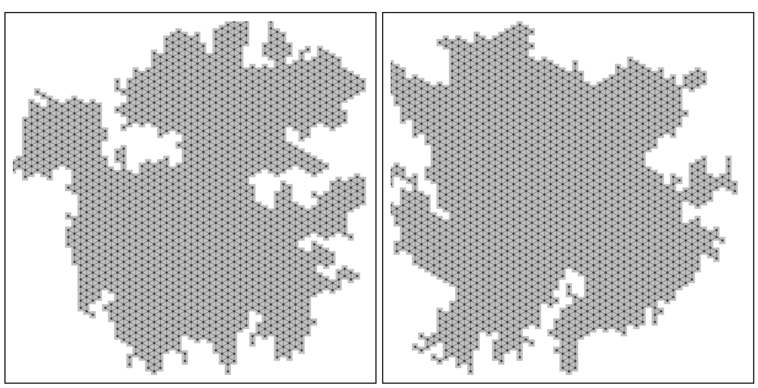


Fig. 6 Two examples of a hexagonal mesh (meaning that any node has exactly 6 possible neighboring locations to which it can be connected) superimposed over an arbitrarily shaped geographical area. In both cases, the square in which the swarm's territory is inscribed is $5km \times 5km$ (for a mesh in which any two connected nodes are $100m$ apart).

The assets, i.e., drones and drone bases, were set as follows: unless stated otherwise, one base is created per km^2 (rounded down), so the number varied between 2 and 20 bases for the aforementioned sample. With regard to the actual placement of the bases, two variations were implemented: (1) purely random and (2) *near optimal*, meaning that, starting from random locations, bases were moved apart following a repulsive field until an approximately even distribution (within the confines of the region of interest) was reached. Unless stated otherwise, the number of drones is equal to the number of bases and their initial location (at which base they start) chosen at random (so it is possible for two drones to start at the same base).

With regard to power consumption and battery charging, each hop incurs a cost of 1 while each time step spent at a base recharges the battery by 1. The autonomy of each drone (at full charge), was set to 60. If considering the $100m$ distance between way points, this corresponds to a total distance travelled per trip of 6 km. If the drones' autonomy is a realistic 30 minutes, this in turn implies a time-unit of 30 seconds and a flight speed of $12km/h$. NB: these values are approximations and are only intended to give the reader a rough idea of the scale at which the proposed system could operate.

4.2 Departure and path planning

The probability to leave the *resting* state after reaching full charge was set so that, statistically, each drone would spend the same time flying, charging and on stand-by, which in turn implies that about one third of the fleet can be expected to be airborne at any one time. Every drone computes its flight plan based on information available from the DT at the time of departure, as per the procedure detailed in Section 3.4.

4.3 Performance measure

For the performance measure we need to reiterate the intended application domain, namely the *continuous* allocation (observation) of locations to schedules such that we minimize the age of the information as much as possible. This value is already recorded for all locations in the DT. This allows us to determine, for any number of time steps, how many locations have not been visited during that period. Conversely, for any fraction of locations we can determine how many steps (on average) it takes such that all locations have been visited at least once.

For example, if there are 6 drones flying concurrently and 120 nodes (roughly covering one square kilometre at 100 m interval), at least 95% (114) will not have been visited less than one time-step ago (possibly more if two or more drones happen to be co-located). If this threshold is increased to one (visited less than two time-steps ago), this fraction could drop at most to 90% (108) since, in the absence of any overlap, both the nodes closest to the drones now and those closest to them one time-step ago will be excluded (and so on and so forth). The rate at which this fraction of "surviving" nodes decreases as the value of the threshold increases is a good indication of performance for the chosen objective of effectively patrolling the area. For example, it is reasonable to say that a distributed algorithm for which, at any point in time (after the system has reached steady state), 50% of nodes will have statistically been visited in the last 100 time-steps is better than one for which reaching the same fraction (0.5) requires extending the threshold to 150 time-steps. Furthermore, this measure can easily be extended to include a wider area around the drones, using a revised formulation such as *"what fraction of nodes have not been within 1, 2, ... , n hops of any drone in the last t time-steps?"* (see Figure 7).

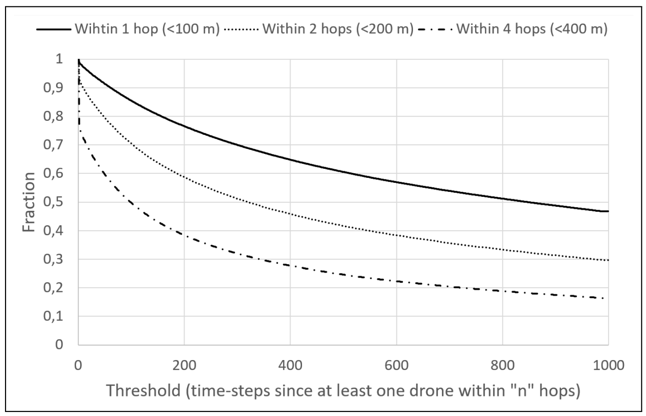


Fig. 7 The performance metric. The *survival* curves indicate the fraction of nodes in the hexagonal mesh (vertical axis) that have not been within 100, 200 and 400 m of at least one drone in the last t time-steps (horizontal axis). E.g., 59% of the area was always beyond one hop of the nearest drone in the last 200 time-steps, 38% if extending the time window to 600 steps (middle curve).

4.4 Data collection

Two hundred independent simulation runs (including the initialisation phase in which the base and drone locations are determined) were conducted for every region in the sample. So for every combination of parameter values, results are compiled from nearly 200k realisations. Each simulation lasted 2000 time-steps, which was found to be sufficient for the system to have reached steady-state.

5 Results and Discussion

The results are the summary of more than 2 million independent simulations, with the tested scenarios being imaginary maps (i.e. not real locations); the results and the discussion is to be seen in this light.

5.1 Benchmark performance analysis

As a benchmark we considered randomly placed bases. As previously stated, 995 simulated environments of varying areas were used, the presented results are the average values from 200 individual runs for each combination of parameter values. Figure 8 plots for each of the tested environments the average number of steps it took (y-axis) to achieve one of three measures of, basically, complete coverage, as a function of the total area of the region of interest (x-axis). Recorded is the time taken to visit 99% of all locations, defined using the increasingly inclusive criteria of having been within 100, 200 or 400m of at least one drone.

It is important to keep in mind that, unless stated otherwise, the ratio between the number of drones and area size remains the same for all simulations (so for significantly larger environments there is also a significantly larger sized swarm). The fact that the approach actually appears to perform better for larger environments is therefore not surprising: the law of big numbers dictates that it will be increasingly unlikely to have all drones (and bases) placed such that some part of the environment remains *unvisited* for a long period.

It is also important to consider the following: the decision to measure when a location was visited, but also when a location was almost visited is motivated by the nature of the approach. We use signals to guide the drones' paths but restrict their movement to a hexagonal mesh. In this constellation we can easily come up with examples where visiting all locations comes at a high cost (i.e., has to go through locations that have recently been visited). We argue that this measure is appropriate for the applications we have in mind, which consider the drones carrying advanced sensing equipment which can operate over distances and thus assess the condition of neighbouring locations.

5.2 Influence of the number of bases and drones

In the benchmark, the ratio between the number of bases and the size of the area was kept constant, with the number of drones equal to the number of bases. This was to quantify the influence that the size of the region of interest has on performance, for a fixed average population density. The obvious next step, particularly with respect to identifying parameter values capable of delivering a target performance in a future real-world deployment, is to relax this fixed population density rule.

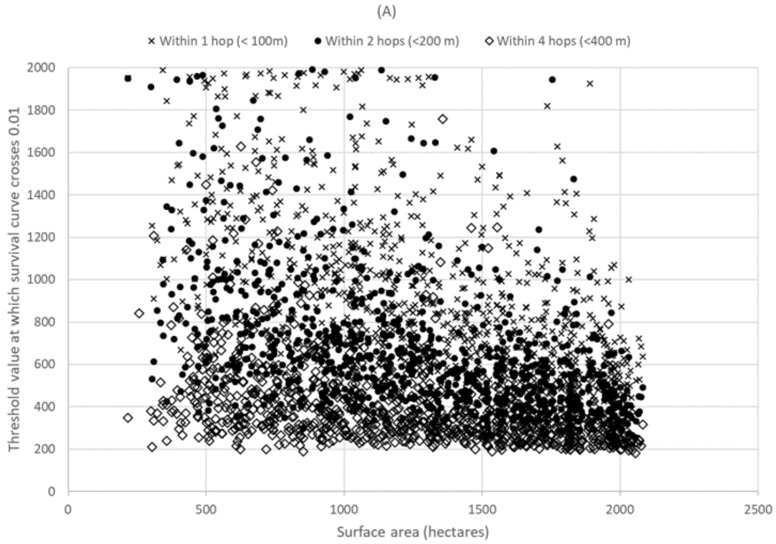


Fig. 8 Shown are the results for starting with a single drone per base and a fixed 'number of bases to mapsize' ratio. 995 simulated environments were evaluated (plotted along the x-axis on the basis of their size, not topology). Recorded are the average performance (over 200 simulations, see Figure 10 for the variance) with regard to the time taken (y-axis) to collect data from 99% of the locations, where the data collection capability was assumed to be such that cells within 1, 2 or 4 hops could be observed. Figure 9 shows results for twice the number of bases or twice the number of drones.

We started by examining two additional scenarios: one in which the number of drones was doubled but the number of bases was kept identical (relative to benchmark values), and one in which the opposite was true (twice as many bases, same number of drones as in the benchmark). The results are summarised in Figures 9 and 10.

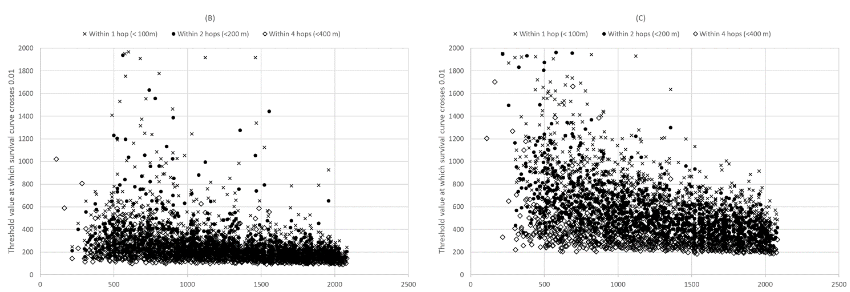


Fig. 9 Identical plot as in Figure 8, but for double the number of drones (left) or double the number of bases (right). Bases are distributed randomly.

Unsurprisingly, increasing the number of drones resulted in a marked performance increase compared to the benchmark. From a qualitative viewpoint this is trivial (having more units can only reduce the time interval required to reach any given level of coverage), but it is informative to compare the gain achieved (as a function of the severity of the criterion) quantitatively. For the least inclusive one ($< 100m$) the performance increased by 62% on average, whilst for the most inclusive ($< 400m$), this figure dropped to 53% (see Figure 10).

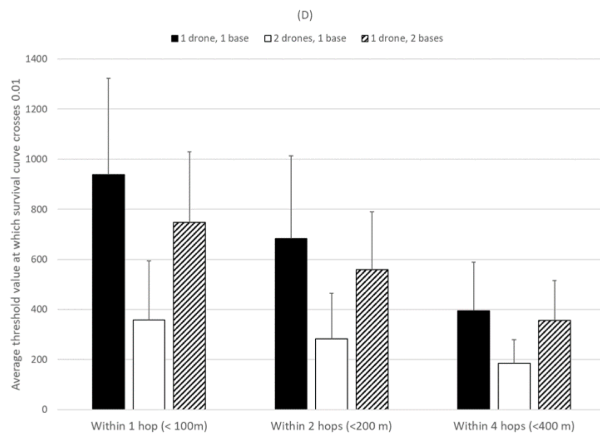


Fig. 10 Performance comparison between the benchmark scenario (full bars), the modified version involving twice the number of drones (empty bars) and the one involving twice the number of bases (dashed bars). The chosen metric is the average value of the threshold time interval for the three criteria. Error bars indicate the standard deviation.

The effect of increasing the number of bases is more interesting and less intuitive: doubling this parameter value appears to result in a significant improvement, reducing the threshold value by an average 20% for the toughest criterion. This is easily explained by more patrol routes becoming available as the number of bases increases, but since the cost of these charging stations is likely to be substantially lower than that of a drone, it also strongly suggests that this approach could be a more efficient strategy to achieve a target performance.

5.3 The impact of base locations

A final set of numerical experiments involved a preliminary exploration of the influence of base placement. The fact that performance generally increases with the size of the region of interest when the number of bases is linearly proportional to the surface area (benchmark scenario) seems to indicate that poor placement could have a strong negative impact. Accordingly, we tested an alternative scheme in which bases are placed so as to approximate an even distribution (see Section 4.1 for details).

Results are shown on Figure 10 and confirm that this modification had a beneficial effect, although it was not as pronounced as anticipated. We believe that this is due to the relatively long range of the drones relative to the typical environment size. This tends to limit the impact of the charging points location, since it makes it less likely that any part of the region of interest is beyond reach, even if it is far from the nearest base. We will seek to confirm this interpretation in future work.

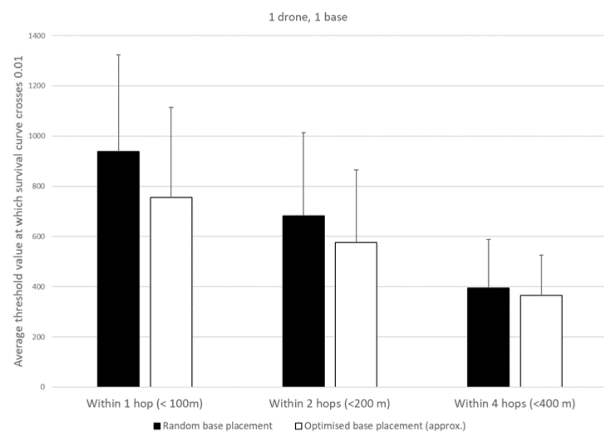


Fig. 11 Comparison between random (full bars) and near optimal (empty bars) base placement.

6 Conclusion

The considerations presented in this paper lay the ground-work for general investigations into path planning for data collection of a collective of cyber-physical systems. Both VTT as well as TNO engage in this theoretical research for reasons related to a large number of projects, involving numerous types and classes of unmanned and potentially autonomously operating vehicles. Applications range from assessing conditions in the environment in real-time (monitoring air quality, looking for gas leaks, surveillance for large industrial terrains) over military intelligence gathering (finding land mines, tracking enemy movement and, ultimately, engaging in armed conflict) to the deployment of intelligent autonomous systems over extremely large distances (in space or on other celestial bodies). All these applications are currently being worked on in some way or the other, and many of these use cases will become reality in the years to come.

6.1 Scope and applicability of the presented idea

The title of this paper intentionally speaks of *multi-robot* systems, as opposed to restricting the applicability of the presented work to swarms of UAVs. Within the scope of the presented work, one might argue the presented approach and the discussed results are more applicable to e.g., ground based drones such as rovers because the provided modelling glosses over a number of issues that UAVs would pose for the practical implementation. E.g., the range of a UAVs is strongly dependent on the wind conditions at the time, and due to this connections between two locations are not symmetric with regard to their incurred energy cost (unlike in our model).

The specific requirements of any use case will determine how, and to which extent an application can be tuned and tailored. Any experts and practitioner in the field knows that after a system is built, optimizing it for the specific use case will often hold the potential for significant performance improvements and will, quite commonly, be what can make the difference between outperforming the competition or being outperformed. With that in mind, we proposed a straightforward, simple mechanism that enables a collective of devices to operate on a shared problem. The approach side-steps all difficult inter-agent negotiation processes (undoubtedly at some cost to the performance) and, due to its simplicity, is inherently robust against unit failure. The need for secure communications is removed, as the devices do not need to communicate for the planning and execution of the plan (which does not prevent drones breaking radio silence when they have spotted something note-worthy).

6.2 Future work

We randomly created almost a thousand maps of different size, and extensively tested various settings for all of them. Even though none of these represents a real-world location or use case, clear trends can be identified. For instance, for constant surface area/swarm size ratio, performance improves as the environment becomes larger. Such results can and will inform current and future projects where case driven approaches have to be designed and implemented. Based on current projects, and those planned / expected in the near future, we consider the following as *future work*:

6.2.1 Realistic cost functions

Realistic cost functions for calculating and planning the routes. This means including relevant environmental conditions such as wind speed and direction, but also using different drone models. A rover on Mars, for example, can simply pause operations and resume them when conditions have improved while a UAV over a battlefield cannot. These investigations will be project driven and probably happen in parallel to investigations of using heterogeneous collectives (either in the equipment the drones carry (not everyone has a temperature sensor) or in their type or class, e.g., using rovers and drones together).

6.2.2 Increasing agent autonomy

Increasing agent autonomy in the sense of endowing the drones with more advanced intelligence and decision making capabilities. Our drones can already carry significant payloads with regard to sensing, as well as data processing, hardware. In the various scenarios presented in this paper, a drone simply follows its planned route, but it seems obvious that in any realistic deployment, future surveillance drones would need to be capable of deviating from their course in response to detecting certain events. Future work will investigate the interplay between the type of orchestration methods described here and the situational awareness and other autonomous features being developed in a variety of other projects at TNO and VTT.

6.2.3 Adding priorities

Adding priorities to be able to have a differentiated view on the map. This has a connection to the previous point as drones could change the priority of a location based on data that they have collected during their journey. We are currently considering local alterations to the signal production or diffusion rate as a convenient route to implement such variable priorities.

6.2.4 Additional investigation of topology and swarm size

We want to continue our systematic exploration of how swarm size impacts performance, and what practical implication this can have (consider, for example, the possibility of altering the number of drones post-deployment, based on information collected at runtime). Furthermore, we are in the process of evaluating a measure of complexity for the generated maps (fractal dimension) that would allow for a more fine-grained investigation of the influence of the region's characteristics than simply considering the total surface area. If successful, applying the same metric to any real map could allow us make statistical predictions about the performance of any given deployment of the proposed solution (swarm size, drone range, number of bases, DT parameter values, etc).

6.2.5 Stochastic versus deterministic planning

In the variation currently used, the paths are planned deterministically based on the signals in neighbouring locations. We are currently investigating a stochastic alternative, which could result in additional flexibility.

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